Modelling human clustering and transfer of task rules

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Motivation

- Real-world environments are complex and high-dimensional.
- But humans solve it effortlessly and efficiently.
- Hypothesis: Humans learn low-dimensional task representations to simplify the tasks.
    - by building abstract and behaviorally relevant representations.

Clustering and transfer of task rules
(Colins & Frank 2016)

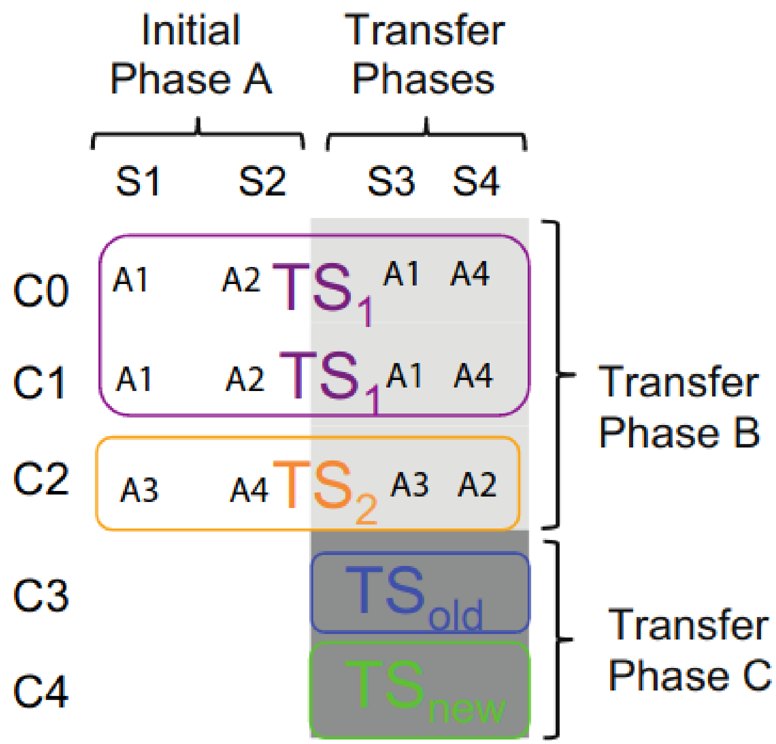
- Learners discover structure to cluster distinct sensory events into a single latent rule set.
  - Transferring learned knowledge to new contexts of the same rule set.
- Key findings (phenomena to model with RNN):
  - Within-cluster transfer of learned rules.
  - Generalization of clusters (learned rules) to novel contexts.
  - Context popularity-based priors (Chinese restaurant process).

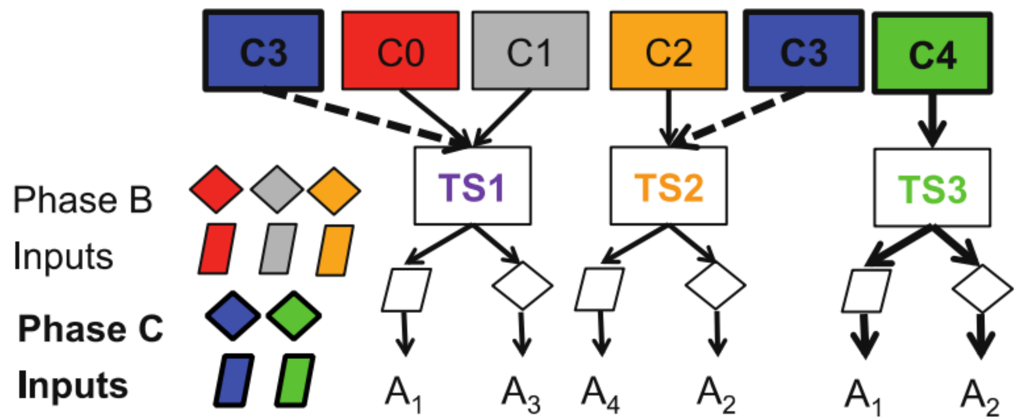
Windows Mac Linux

Plan

1. Train ANNs with RL and supervised learning to perform the task in Collins & Frank 2016.
2. Analyze internal representations of the RNN
   - Whether they exhibit similarity structure across different contexts but shared the same rule set.
   - Examine RPEs in the RNN to determine whether they show sensitivity to hierarchical structure in a way like EEG patterns from Collins & Frank 2016.
3. Modify the ANNs to allow it to display a clustering prior (e.g. Chinese restaurant process) for novel contexts
4. Fit other ANNs directly to the behavioral data, and compare it with RNN trained to perform the task.

Task in Collins & Frank 2016.

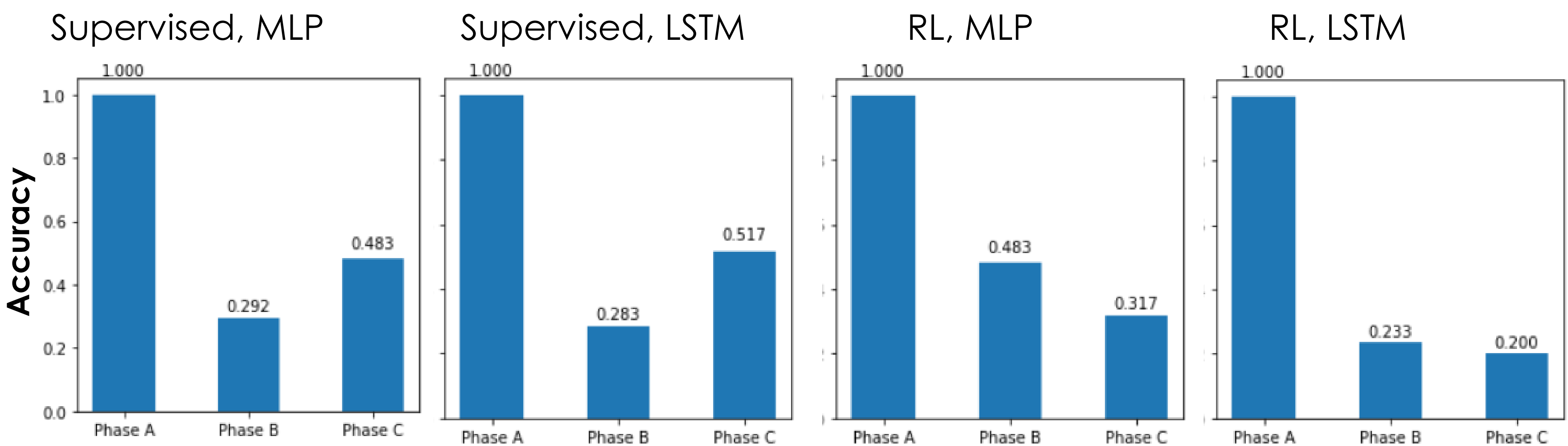




Train ANNs with supervised learning and RL to perform the task

- Architecture:
  - Supervised: MLP or LSTM with 1 or 2 layers.
  - RL: Actor-critic consists of 1 network (MLP or LSTM) with 1 or 2 layers.
- Pipeline:
  1. Phase A: Train 200 trials and converged.
  2. Phase B: Train 200 trials and converged.
  3. Phase C: Train 200 trials and converged.
- Converged?
  - Supervised: 10 consecutive trials with cross-entropy loss less than 0.01.
  - RL: 10 consecutive trials with accuracy larger than 0.9.

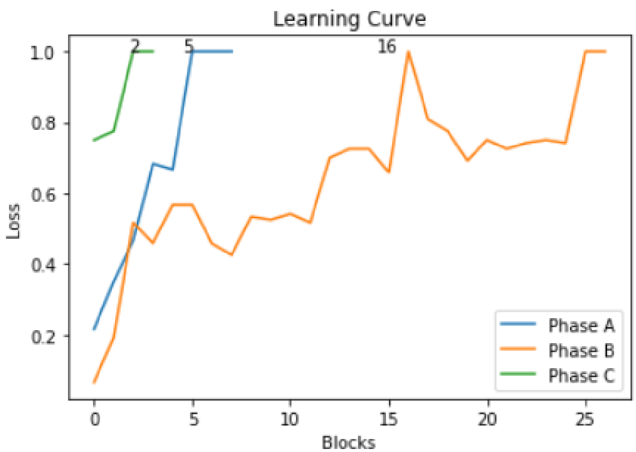
Overall transfer after initial trained on Phase A



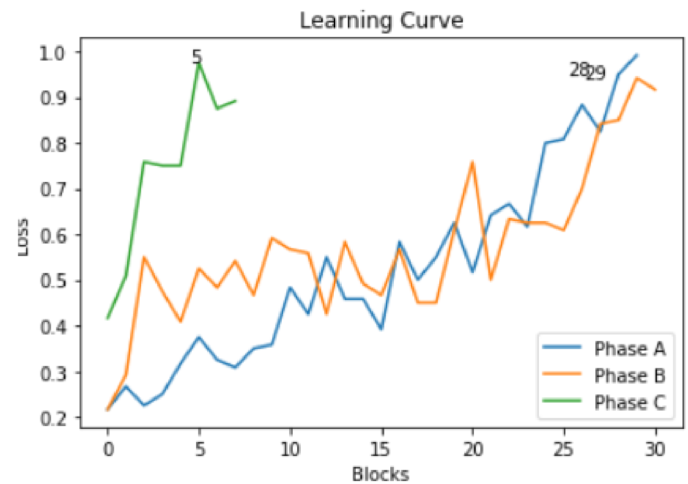
2-layers has best performance
and generalization.

Learning curve: overall transfer

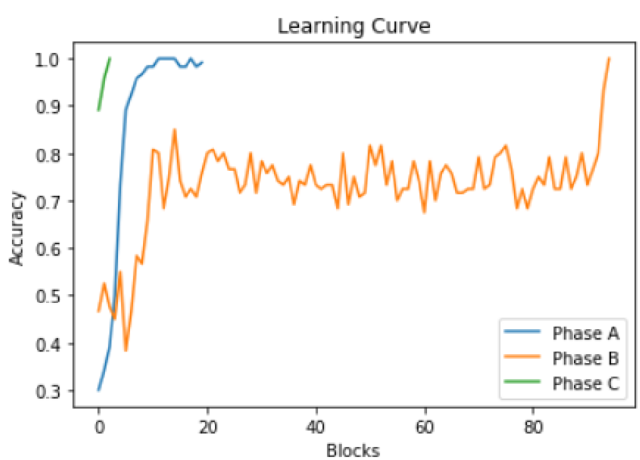
Supervised, MLP



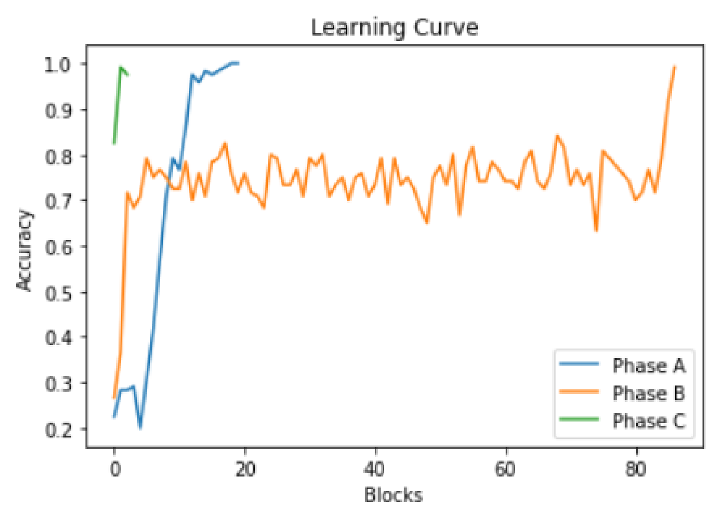
Supervised, LSTM



RL, MLP



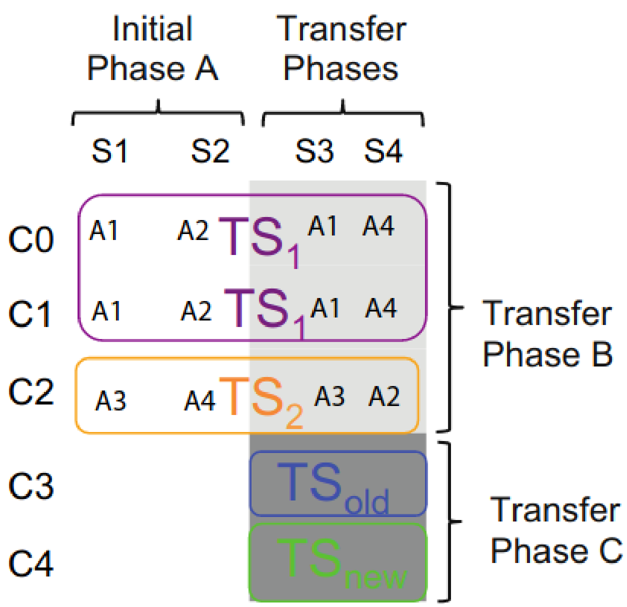
RL, LSTM

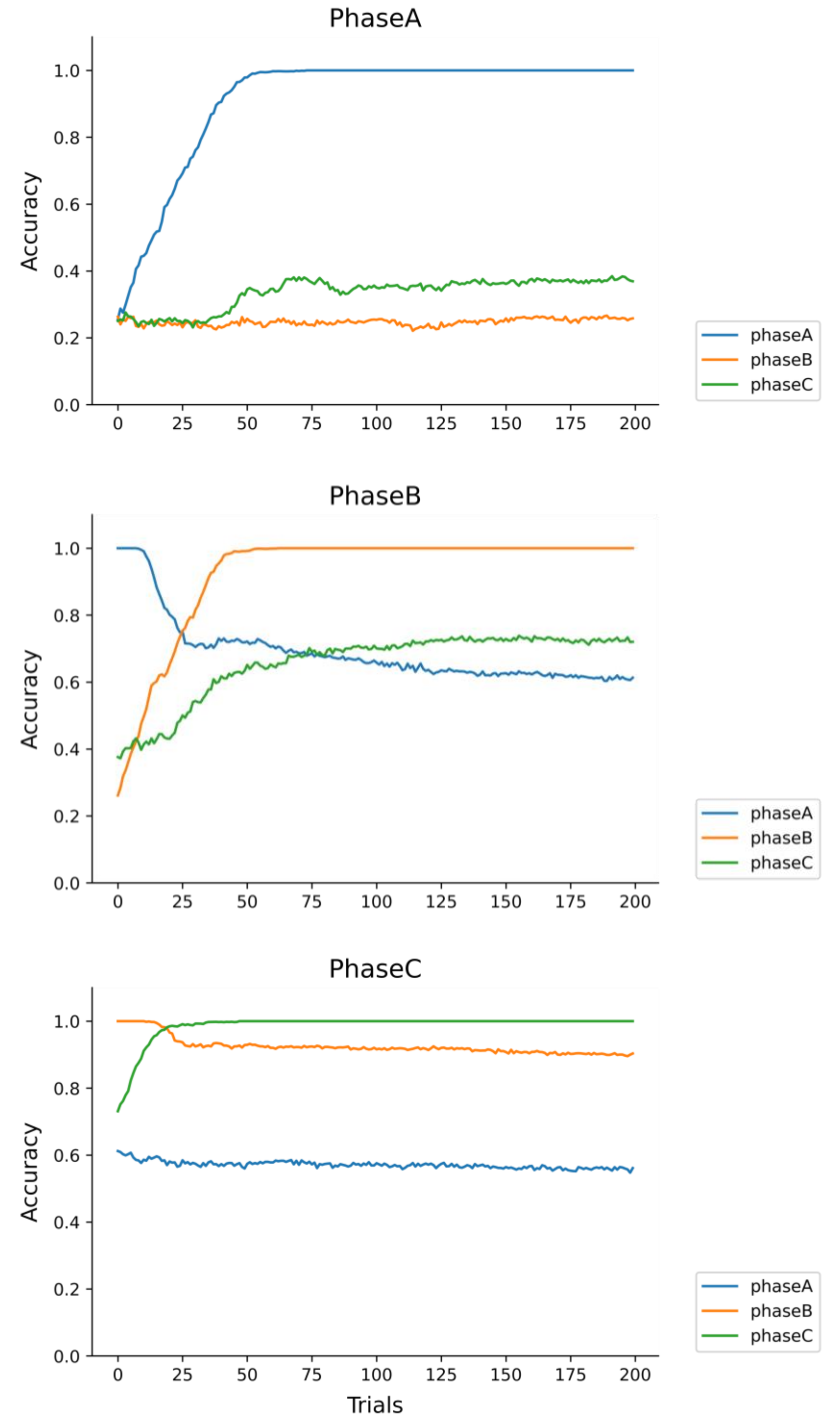


- Due to:
  - Similar behaviors of architectures and training algorithms (supervised learning and RL)
  - Slow training speed of RL algorithm.
  - **Limited time**
- Further analyses based on 1-layer LSTM trained by supervised learning.
- And the results are the average of 100 LSTMs being random initialized.

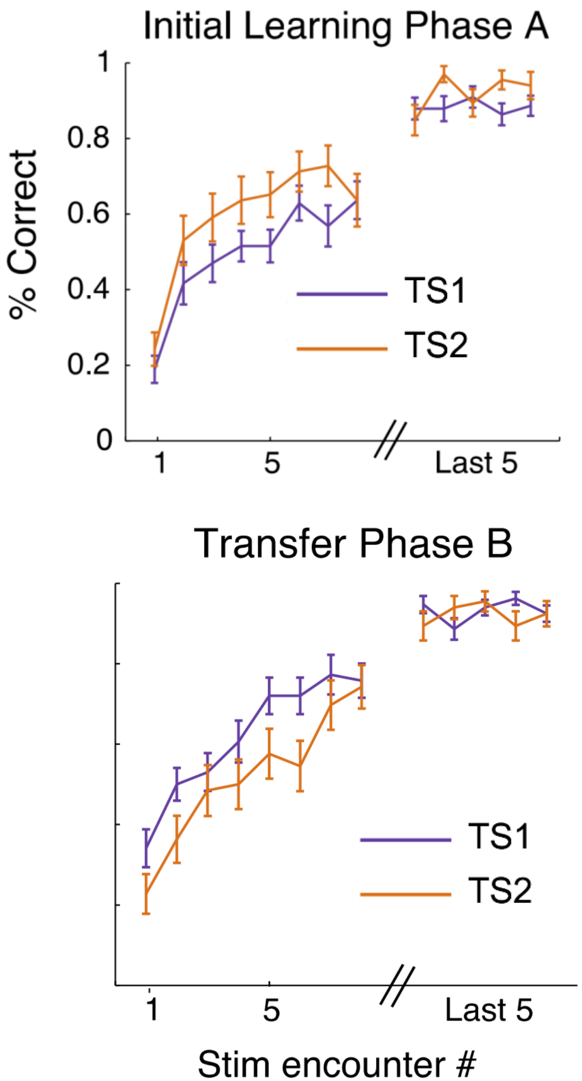
Learning Curve

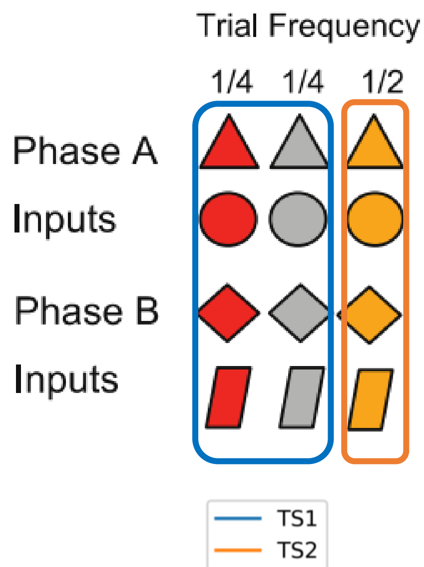
- Effect of per training sample on accuracy in 3 phases.

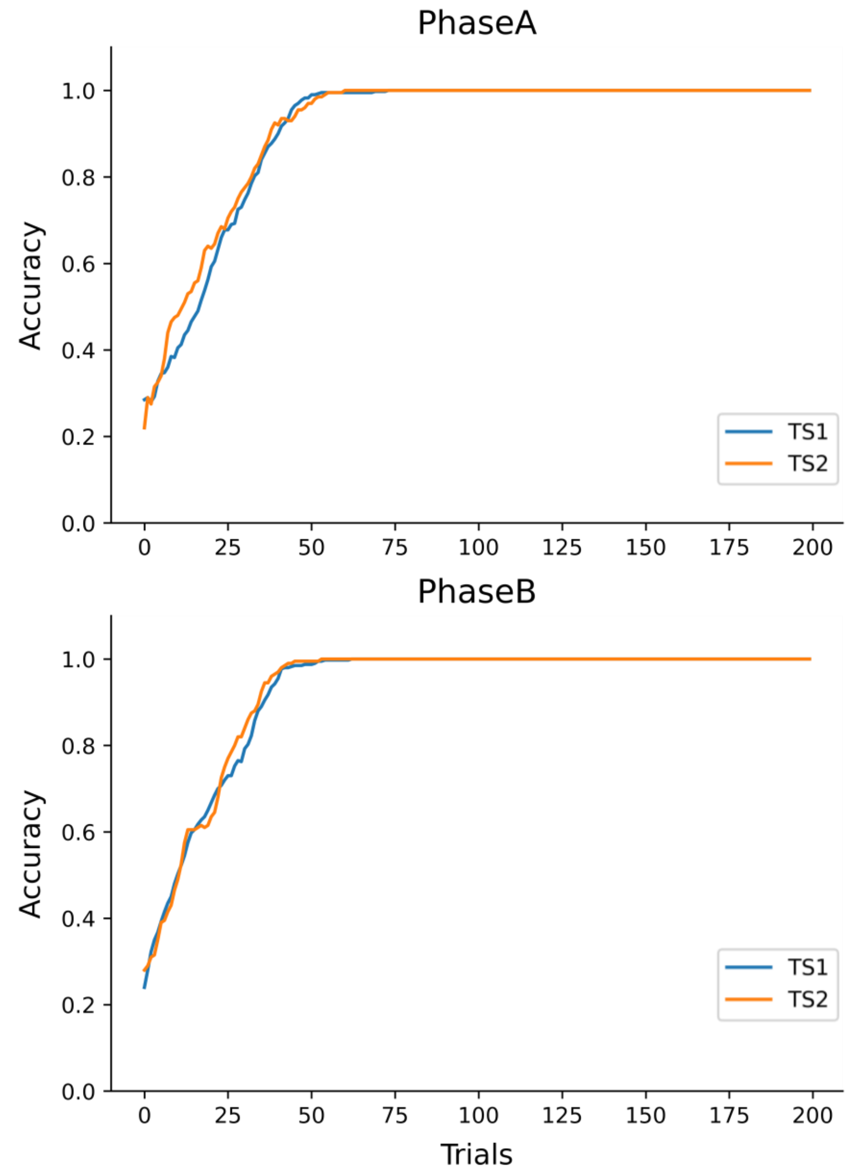




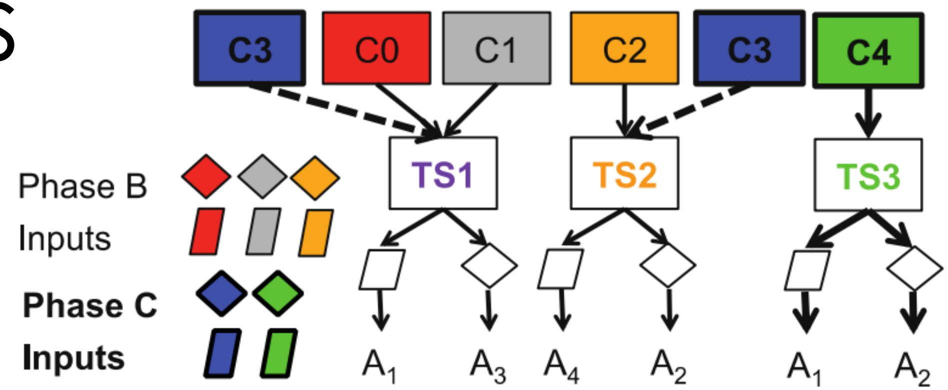
Transfer of two task sets

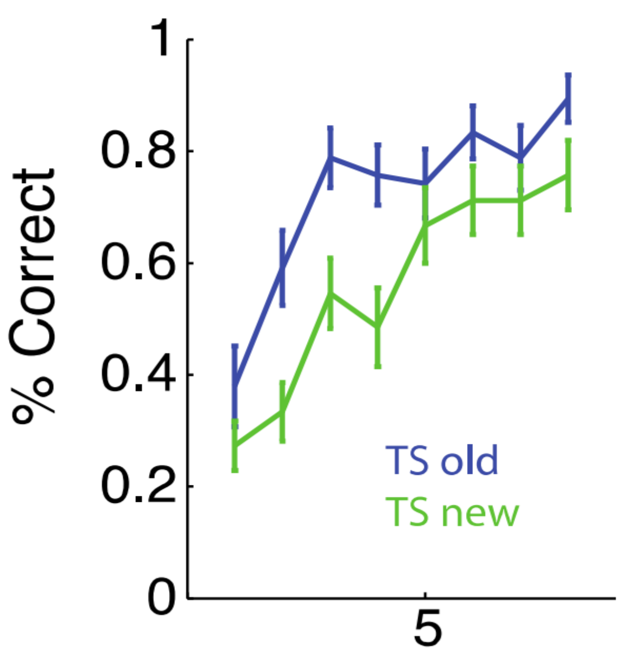


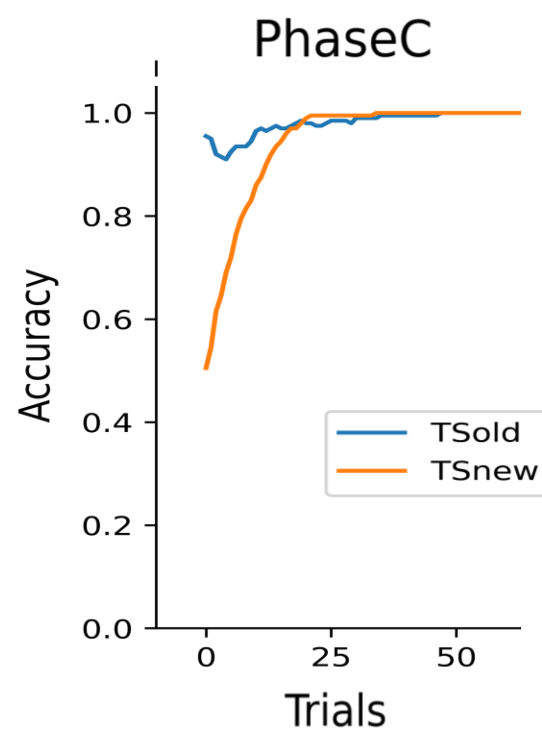




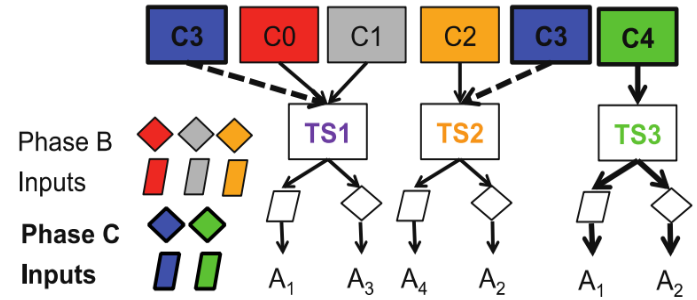
Transfer to novel contexts and clustering priors

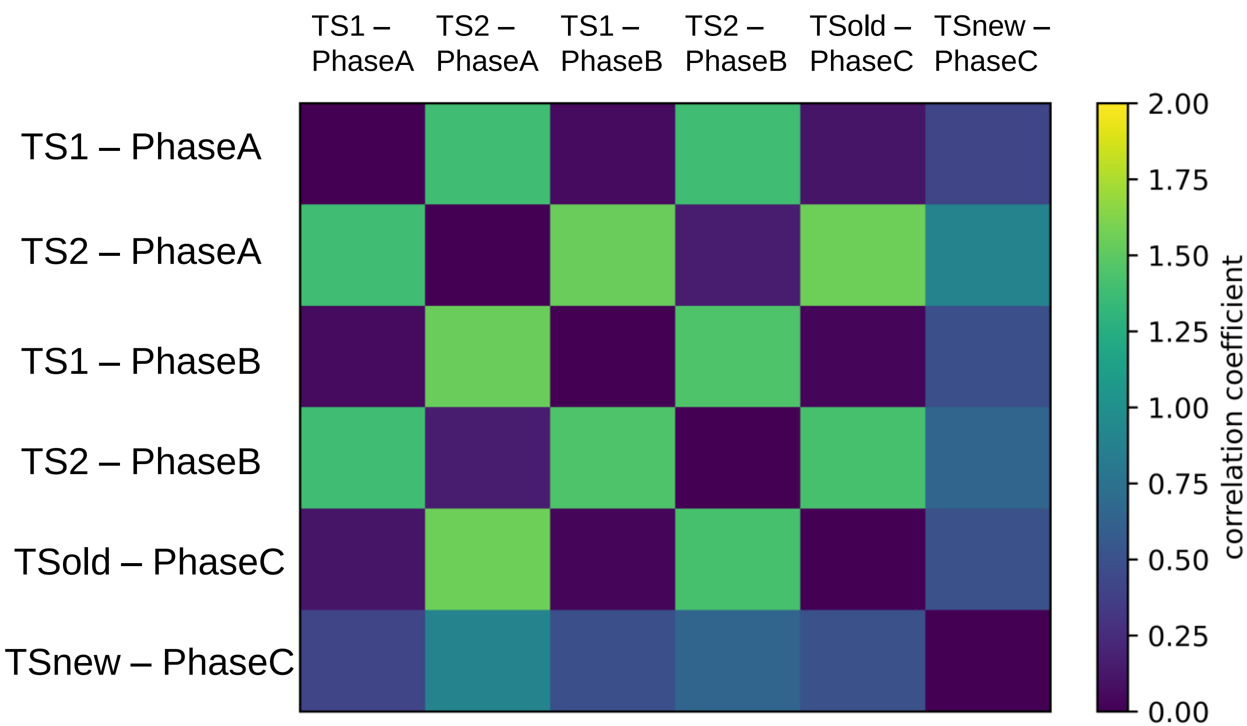


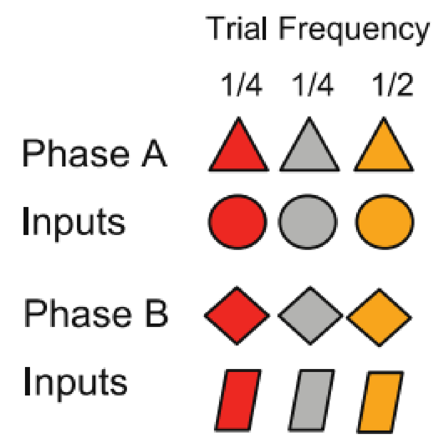




Shared representations of task sets







Future plan

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